Visual Working Memory in Action: Investigating Identity Judgments across Fingerprints, Faces, and Paintings

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Abstract

Fingerprint experts are skilled at matching fingerprints in a variety of contexts, including when prints are briefly shown, are inverted or visually noisy, and can discriminate between prints from the same individual but from different fingers (i.e., Smith's thumb and index finger). This ability has been attributed to superior working memory; however, theoretical models of visual working memory rely only on basic visual stimuli. What happens when these theoretical models are applied to real-world stimuli? This experiment tested whether increasing the amount of visual information available to people, from two to four to six spotlight samples of an image, improved their identification judgements across three stimulus types: fingerprints, faces, and paintings. As informational load increased from two to four to six spotlight samples, people were more accurate at determining whether the two images depicted the same identity. However, their confidence ratings were not aligned with their accuracy, suggesting a complex relationship that may be explored in future research through the application of signal detection models. Our findings supported summary-based encoding models of visual working memory, suggesting that when it comes to complex stimuli, we rely on summary statistics in encoding visual landscapes rather than encoding items independently. We also found that increasing visual informational load in the process of making identification decisions resulted in improvements in identification judgements across a broad range of naturalistic stimuli (namely, fingerprints, faces, and paintings). This experiment specifically provided a potential explanation for how fingerprint experts achieve such remarkable feats utilising their visual working memory.

Keywords: visual working memory, informational load, identification judgements, real-world stimuli, fingerprints.

Declaration

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Contributor Roles Table

ROLE	ROLE DESCRIPTION	STUDENT	SUPERVISOR 1	SUPERVISOR 2
CONCEPTUALIZATION	Ideas; formulation or evolution of overarching research goals and aims.	X	X	
METHODOLOGY	Development or design of methodology; creation of models.	X	X	
PROJECT ADMINISTRATION	Management and coordination responsibility for the research activity planning and execution.	X	X	
SUPERVISION	Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team.		X	
RESOURCES	Provision of study materials, laboratory samples, instrumentation, computing resources, or other analysis tools.		X	
SOFTWARE	Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code.		X	
INVESTIGATION	Conducting research - specifically performing experiments, or data/evidence collection.	X		
VALIDATION	Verification of the overall replication/reproducibility of results/experiments.	X	X	
DATA CURATION	Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later re-use.		X	
FORMAL ANALYSIS	Application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data.	X		
VISUALIZATION	Visualization/data presentation of the results.	X	X	
WRITING – ORIGINAL DRAFT	Specifically writing the initial draft.	X		
WRITING – REVIEW & EDITING	Critical review, commentary or revision of original draft	X	X	

Introduction

Expertise in fingerprint analysis

Fingerprint analysis is often portrayed in the media as a task conducted solely by computers. However, when a latent fingerprint is found at a crime scene, fingerprint experts are required to examine the print and compare it to prints in the possession of the police. These experts are skilled at matching fingerprints in a variety of contexts, including when prints are shown briefly (Thompson & Tangen, 2014), are inverted or visually noisy (Busey & Vanderkolk, 2005), and they are even able to identify prints that belong to the same individual albeit from different fingers (e.g. index and ring; Searston & Tangen, 2017). Similar to experts in other domains, such as chess (e.g., Chase & Simon, 1973), fingerprint examiners also exhibit superior visual working memory for fingerprints (Thompson & Tangen, 2014).

That examiners exhibit superior memory for fingerprints is interesting because the examination process involves a side-by-side comparison of an unknown crime-scene print and fully-rolled prints from candidates known to police. There is no opportunity to learn (or remember) an individual’s prints over time because each case typically involves a new identity. It is possible that fingerprint experts have better visual working memory capacity in general, however, their expertise in a variety of visual tasks appears to be limited to domain-specific stimuli (Searston & Tangen, 2017). Another possibility is that their ability is the result of experience with the comparison process itself, which likely recruits visual working memory processes as the examiner shifts their attention between prints.

While there is a rich literature on visual working memory in general, little is known about the boundary conditions of visual working memory in the context of fingerprint analysis or other real-world tasks involving novel identity judgements. The current project bridges this gap by testing the limits of visual working memory for complex visual information - such as fingerprints - in an identification task.

Theoretical models of visual working memory

There are many well-established theoretical models of visual working memory, often falling under one of two theoretical umbrellas. Slot-based models, such as discrete resolution models (e.g., Alvarez & Cavanagh, 2004; Zhang & Luck, 2008), propose that working memory is constrained in capacity by the number of items able to be simultaneously held. The number of available slots is fixed, often theorised to be around four (see Miller, 1956; Alvarez & Cavanagh, 2004). Based on a change detection paradigm, each 'slot', according to such models, is thought to hold a single item with a fixed level of detail, with each item being considered entirely independent. These models regard the encoding of such items as all or none, an object is either encoded and remembered accurately, or isn't encoded or remembered at all (Ma et al., 2014). In contrast to slot-based models, resource models of working memory, such as flexible resource models (e.g., Wilken & Ma, 2004; Bays & Husain, 2008) posit that rather than the capacity limit of working memory being dictated by the number of items able to be held and encoded at a given time, it is the allocation of resources that dictates the precision of memory (Ma et al., 2014). In such models, memory resources are flexibly deployed, with the individual voluntarily controlling which items are prioritised over others, resulting in more accurate recall of prioritised items. This, however, comes at the cost of other items which are de-prioritised and therefore encoded less precisely (Ma et al., 2014).

Flexible deployment of memory resources forms the basis of summary-based encoding models (e.g., Ariely, 2001; Parkes et al., 2001), which argue that we encode and store summary statistics informative of entire visual landscapes in addition to individual items, regardless of whether individuals are prompted to only remember items individually (Brady & Tenenbaum, 2013), thereby generating a more efficient representation of complex visual information. It is this acknowledgement that informational items cannot be recalled independently in the case of complex stimuli that sets summary-based encoding models apart from other theoretical models, and deems them the most relevant to real-world contexts, such as forensic identification decisions, where complex stimuli are abundant. Indeed, flexible deployment of memory resources are thought to be a justification for why experts are able to achieve such remarkable feats in their domains of expertise. Experts are thought to achieve superior memory by developing the ability to chunk pieces of information together, enabling more efficient encoding of domain-relevant information (Chase & Simon, 1973). While a novice can simultaneously hold up to four or five chunks in their working memory for the purpose of completing a task, experts, through deliberate practice (Ericsson & Lehmann, 1996), develop complex, domain-specific chunks, termed “mental representations” (Ericsson & Pool, 2016) that are encoded into their long-term memory. When approaching tasks that involve the use of information from their domain of expertise, experts retrieve these mental representations, freeing up space in their working memory to enable higher-order processing, organisation of information, and analysis.

Rather than considering the complexity of fingerprint matching tasks, most of these aforementioned theoretical models have been extensively tested in the context of a change detection paradigm using basic visual stimuli (e.g., Miller, 1956; Ma et al, 2014; Brady & Tenenbaum, 2013). In such tasks, participants are shown a sample array (e.g., a set of coloured squares) for a set amount of time (e.g., 100ms). Participants are then provided with a blank delay interval or fixation point for a set amount of time (e.g., 900ms) to allow sufficient time for encoding into visual working memory, before being shown a test array either identical to the sample array, or featuring a simple change (e.g., the colour of a square). Participants are then tasked to identify whether the sample array and test array are identical, or whether a change occurred (see, e.g., Luck & Vogel, 1997). Performance is typically measured by way of a capacity estimate that translates to the number of items that each individual can successfully retain in their visual working memory (Balaban et al., 2019).

As theoretical models posit that informational capacity limits are fundamental to the conceptualisation of visual working memory, a key variable typically manipulated in change detection tasks is informational load. Informational load, defined as the ‘perceptual complexity of visual stimuli’ (Eng et al., 2005), refers to the amount of information individuals are required to process and hold in their working memory during a given task. As informational load increases so too does the amount of information that must be processed and held in working memory for the task to be completed. Manipulations of informational load in working memory studies can involve incrementally increasing the number of objects present in a visual display (e.g., increasing the number of coloured squares featured in a test array; Luck & Vogel, 1997) or systematically reducing the resolution of images shown to participants (see e.g., Searston et al., 2019). In a forensic context, informational load may be manipulated by dividing an image of a fingerprint into smaller visual chunks, and dictating how many chunks are shown to fingerprint experts in a matching task. Indeed, in this experiment, to emulate such a forensic context, informational load will be manipulated by increasing the visual chunks, hereafter referred to as “spotlight samples”, presented to participants.

Change detection tasks are also based on the assumption that individuals process and encode items singularly and independently into their working memory (Brady & Tenenbaum, 2013). This assumption of independence has since been disproved through behavioural evidence that even in the context of simple visual displays, items are not dealt with independently (Brady & Tenenbaum, 2013). Instead, research has suggested that in contrast to the simple displays utilised in change detection tasks, in the context of real-world stimuli, working memory depends on the prior background knowledge, experience, and perceptual organisation of the individual in regard to the stimulus type. Therefore, in this experiment, stimulus type will serve as a secondary manipulation to enable exploration of the extent to which informational load affects visual working memory across domains. Aside from the inclusion of fingerprint images as the inspiring context, face images will be utilised to enable generalisation of findings to similarly biometric stimuli that participants will have more background knowledge and experience in analysing. Finally, painting images will be utilised to generalise the findings to non-biometric stimuli that are nevertheless encountered in daily life.

The change detection paradigm to measuring visual working memory capacity has been shown to be stable for individuals across time points, and across the population more generally (Balaban et al., 2019), however, these findings cannot be generalised to real-world, complex visual stimuli. Other than the differing category of stimulus being detected (basic stimuli compared to complex stimuli), the main factor that distinguishes fingerprint analysis from traditional change detection tasks is the difference in focus of the task itself. While the goal of a change detection task is to notice and identify changes between two sets of visual arrays, fingerprint matching involves the ability to discriminate between stimuli. Rather than two intentionally identical or nearly identical visual arrays, fingerprint matching tasks involve two different images that may or may not be from the same source identity, whether that be the same finger or person (see e.g., Searston & Tangen, 2017). It is the goal of the individual to utilise their visual working memory to discriminate between signal (i.e., visual information that aids correct identification decisions) and noise (i.e., visual information that hinders correct identification decisions) in order to achieve to the correct conclusion. As a result of the distinction between these tasks, it is unclear how these theoretical models of working memory will fare when applied to complex stimuli.

This project seeks to address this gap in the literature by analysing different theoretical working memory models in the context of tasks involving identification judgements utilising naturalistic, real-world stimuli, such as fingerprint analysis.

The current study

Aims

The current experiment investigates the effects of informational load (i.e. the number of spotlight samples provided in the trial display) on participant identification judgements in a recognition memory task. The aim of this experiment is to better understand encoding limits on visual working memory for complex visual information in an identification task. Stimulus type (i.e. fingerprints, faces, or paintings) will serve as a secondary manipulation. While stimulus type is not a critical factor in testing our hypotheses, exploring informational load across a few different contexts enables us to draw more general conclusion about the way that it constrains working memory in identification judgments. Especially given that prior research has suggested that there may be differences in how individuals encode visual information in working memory depending on the complexity of the stimuli.

The knowledge generated from this experiment will contribute to the broader understanding of visual working memory and its implications in real-world contexts, such as fingerprint analysis in forensic investigations.

Predictions

While visual working memory models have largely been developed in the context of a change-detection paradigm using discrete and basic visual stimuli (e.g. coloured squares, line orientation, individual objects), we can extrapolate from their theoretical basis to make predictions in our experiment about how informational load might affect the encoding of identify information:

1. Discrete resolution models (e.g., Zhang & Luck, 2008; Alvarez & Cavanagh, 2004): According to these models, there is a fixed number of slots in visual working memory, each holding a single item with a fixed level of detail. Thus, as informational load increases, sensitivity should remain relatively stable until the capacity limit is reached (potentially around four items; see Miller, 1956; Alvarez & Cavanagh, 2004). Beyond the capacity limit, sensitivity to identity changes would be expected to decline.

2. Flexible resource models (e.g., Wilken & Ma, 2004; Bays & Husain, 2008):

   These models predict that as informational load increases (from two to four to six visual spotlight samples), the precision of memory for the stimuli will decrease due to the distribution of resources across a larger number of spotlight samples. This decrease in precision would lead to a decline in sensitivity in the current experiment as informational load increases.

3. Summary-based encoding models (e.g., Ariely, 2001; Parkes et al., 2001):

   These models predict that as the informational load increases, participants will rely more on summary statistics to make their judgments. This could potentially result in better sensitivity to identity changes (AUC) as the load increases since participants would have access to more summary information that is diagnostic of identity. However, it is also possible that sensitivity to identity changes would depend on the degree to which the summary statistics are informative and representative of the individual items in the stimuli, which may vary across the different stimulus types (fingerprints, faces, and paintings).

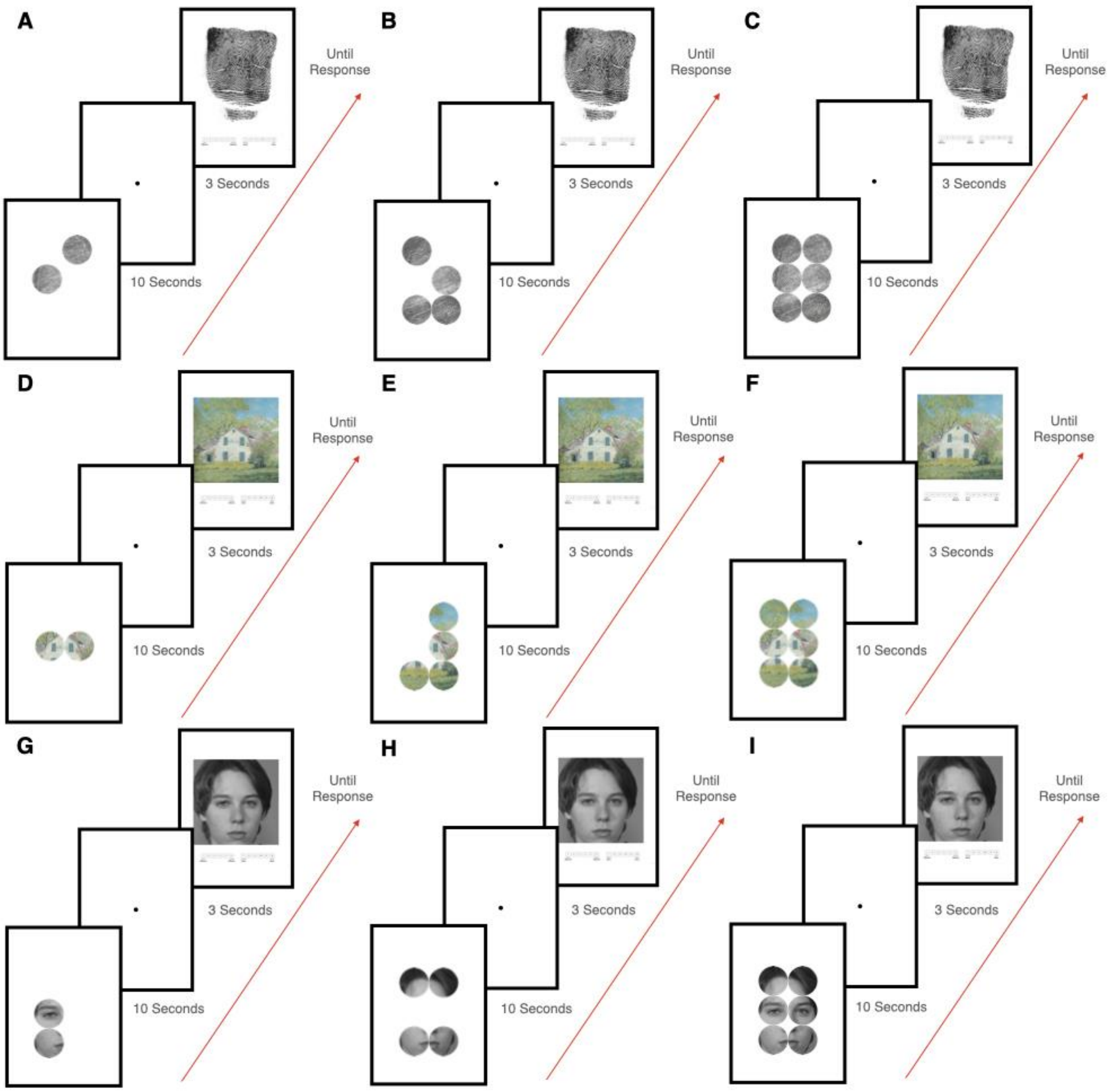
In line with summary-based encoding models (e.g., Ariely, 2001; Parkes et al., 2001), we predict that individuals ’identification judgments will improve as informational load is increased by virtue of the increased access to summary information most useful for generalising across different instantiations of an identity.

Method

In this experiment, we probe working memory limits for fingerprints, faces, and paintings in an identification task. Participants are presented with a ‘probe’ image for 10 seconds, followed by a fixation point for three seconds, followed by a ‘test’ image. In the fingerprint variant of the task, the probe and test images are always two different fingerprint images that are sampled either from the same individual (e.g., Smith’s right thumb on two different occasions) or two different individuals (Smith and Jones’ right thumb). Participants are tasked to decide if the probe and test images are from the same or different fingers, consistent with fingerprint matching tasks. Likewise, in the face variant of the task, the probe and test images are always different face images depicting either the same individual (e.g., two different images of Smith) or different individuals (e.g., images of Smith and Jones). Participants are tasked with deciding whether the probe and test images depict the same person or different people. The paintings are also always different paintings from probe to test, attributed to the same artists (e.g., two different paintings by Smith) or different artists (e.g., a painting by Smith and a painting by Jones). In the case of paintings, participants are tasked to decide if the probe and test images are by the same artist or by different artists. All three variants of the task require participants to decide whether the probe and test images share the same identity or not. Participants indicated this decision, and the confidence with which they made it, through selecting a number on a 12-point forced-choice scale. Critically, we manipulated informational load across all three variants of the task by varying the amount of information provided in the probe image. Rather than seeing the full image, participants are presented with either two, four, or six circular spotlights subsamples from the probe image (see Figure 1 below for an illustration of this manipulation). The order of the three blocks was randomised and counterbalanced across participants.

Figure 1

Visual displays across Information Load and Stimulus Type



Note. A visual depiction of each condition in the experiment. The stimuli conditions are represented in horizontal panels, with A-C depicting the fingerprint block, D-F the paintings block, and G-I the faces block. The informational load conditions are depicted in vertical panels, with A, D, and G depicting 2 visual chunks, B, E, and H depicting 4, and C, F, and I depicting 6. Participants progressed through each trial in the order demonstrated by the red arrows, beginning with the visual display of chunks (10 seconds), followed by the fixation point (3 seconds), and finally the full target image (until response). Dimensions of stimuli images in this figure have been edited for visual clarity.

Design

The experiment consisted of a 3 (informational load: 2, 4, or 6 spotlight samples) × 3 (stimuli: fingerprints, faces, paintings) fully within-subjects experimental design. All participants completed all experimental blocks. As we investigated the effect of informational load on identification decisions, "success" in participant performance was measured by their relative sensitivity to "same" identity trials across conditions.

Participants

Participants were 30 (23 female, 7 male) first-year psychology students at the University of Adelaide, as well as a convenience sample of family and friends of the research team. Participants were aged from 17 to 60. Undergraduate participants were recruited through the university Research Participation System, and were compensated with course credit. Ethics approval was granted by the University of Adelaide's Low-Risk Human Research Ethics Subcommittee (HREC 23/64).

Power Analysis

A power analysis was conducted to estimate the appropriate sample size for detecting a moderate effect ($\eta_p = .06$) of informational load with >80% power using a repeated measures ANOVA. Moderate to large effect sizes are typical of working memory studies (see e.g., Searston et al., 2019). We conducted this analysis using the PWR package in R (Champely, 2022). This analysis indicated that 28 participants would be required to test the primary effect of interest (informational load). We aimed to test 30 participants to facilitate randomisation and counterbalancing across each block in our experiment.

Randomisation and Counterbalancing

In total, participants completed 144 trials. The fingerprint, face, and painting variants of the task were presented in three separate blocks, one after the other. The order of these blocks was randomised and counterbalanced across participants (i.e. one participant might encounter the faces block first, then paintings, then fingerprints, while another might encounter the paintings block, then fingerprints, then faces. Within each block of the experiment, participants completed 48 trials. On a random half (24) of those trials, the target image was a different image of the same identity (the same finger, individual, or artist). On the other half of trials, the target image was an image of a different identity (a different finger, individual, or artist). The order of same versus different trials within each block was randomised for each participant.

The informational load manipulation was also subject to randomisation. Within each block, 16 trials included two spotlights in the probe display, 16 trials included four spotlights, and 16 trials included all six spotlights. The order of these trials was randomised for each participant within each block. Additionally, the probe and display images were randomly sampled from a larger pool of images (described in Materials below), such that each participant encountered different images in the task. Random sampling of stimuli and random presentation of stimuli per participant helps to ensure our results are more robust to image artefacts and image order effects.

Materials

Participants completed the experiment (coded using LiveCode software) on a Macbook Pro 13-inch laptop with noise-cancelling headphones. All images were edited in Photoshop to have standardised dimensions of 900 × 900 pixels, with the circular mask within each image comprising of 300 × 300 pixels.

Fingerprints

The fingerprint images were a subset of 30 same finger and 30 different finger pairs sourced from the Forensic Informatics Biometric Repository (Thompson et al., 2011). The original database consists of 195 fingerprint trios, comprising of a latent print (the type lifted from crime scenes), a matching tenprint (the type generated at a police station), and a highly similar non-matching print. For this experiment, we chose to use random non-matching prints, instead of highly similar non-matching prints to ensure sufficient room for variability in sensitivity across conditions (as highly similar non-matches are notoriously difficult for novices; Thompson & Tangen, 2014). Instead, the print pairs were manually selected based on their visual clarity. A random half were then assigned a non-matching tenprint twin, and the other half were matched with a matching tenprint twin from the same finger. The fingerprint images presented to each participant were randomly sampled from this subsample of fingerprint pairs.

Faces

The face images were a subsample of 50 same identity and 50 different identity pairs sourced from the Face Recognition Grand Challenge database (Phillips et al., 2005), which consists of 50,000 greyscale images of Caucasian individuals. All face images were eye aligned to ensure consistency in the facial dimensions featured across spotlight samples. The face images presented to each participant were randomly sampled from this subsample of face images.

Paintings

The painting images were a subset of 54 same artists and 54 different artist pairs sourced from an extensive database generated by Jessica Marris for her 2015 Honours Thesis at The University of Queensland. Our subset included an equal number of cubist, impressionist, realist, and renaissance artworks to enable randomisation and counterbalancing across participants. Thus, the painting images presented to each participant were randomly sampled from this subsample of images.

Measures

Participant responses on each trial were recorded using a 12-point forced-choice confidence rating scale ranging from 1 (Sure Different) to 12 (Sure Same) with 6 (Unsure Different) and 7 (Unsure Same) serving as the midpoints of the scale. Participant confidence ratings from this scale were then used to compute the empirical Area Under the Curve (AUC) as a measure of their sensitivity to identity changes in identity across the experiment. In order to compute this measure, the scale was further divided into two domains; “Different”, indicated by a response of 1-6, and “Same”, indicated by a response of 7-12. An AUC score of 1 indicates perfect sensitivity (i.e., participants' ability to discriminate same versus different identity trials). By contrast, an AUC score of .5 would indicate chance performance. AUC has often been utilised as a measure of performance in the working memory literature as it accounts for the full range of participant confidence ratings (Searston et al., 2019).

Procedure

Participants were sat at a table and provided with a Participant Information Sheet which they were prompted to read (Appendix A). If they agreed to continue with the experiment, they were provided with noise-cancelling headphones that were connected to a MacBook Pro 13-inch laptop. They provided demographic information before proceeding to watch an instructional video (YouTube link: https://youtu.be/vbM88035tJc). When the video finished, participants completed the first block of trials for the identification task. At the beginning of each trial block, participants were provided with relevant instructions. Each block contained 48 trials, with 144 trials in total. Participants were able to view a progress bar in the bottom right of the screen during the experiment to monitor their progress. The experiment took approximately 40 minutes to complete. When they completed all three blocks, participants were asked if they had any questions, and student participants were granted course credit. This procedure is represented in Figure 1 above, which depicts each trial block as participants encountered them.

Results

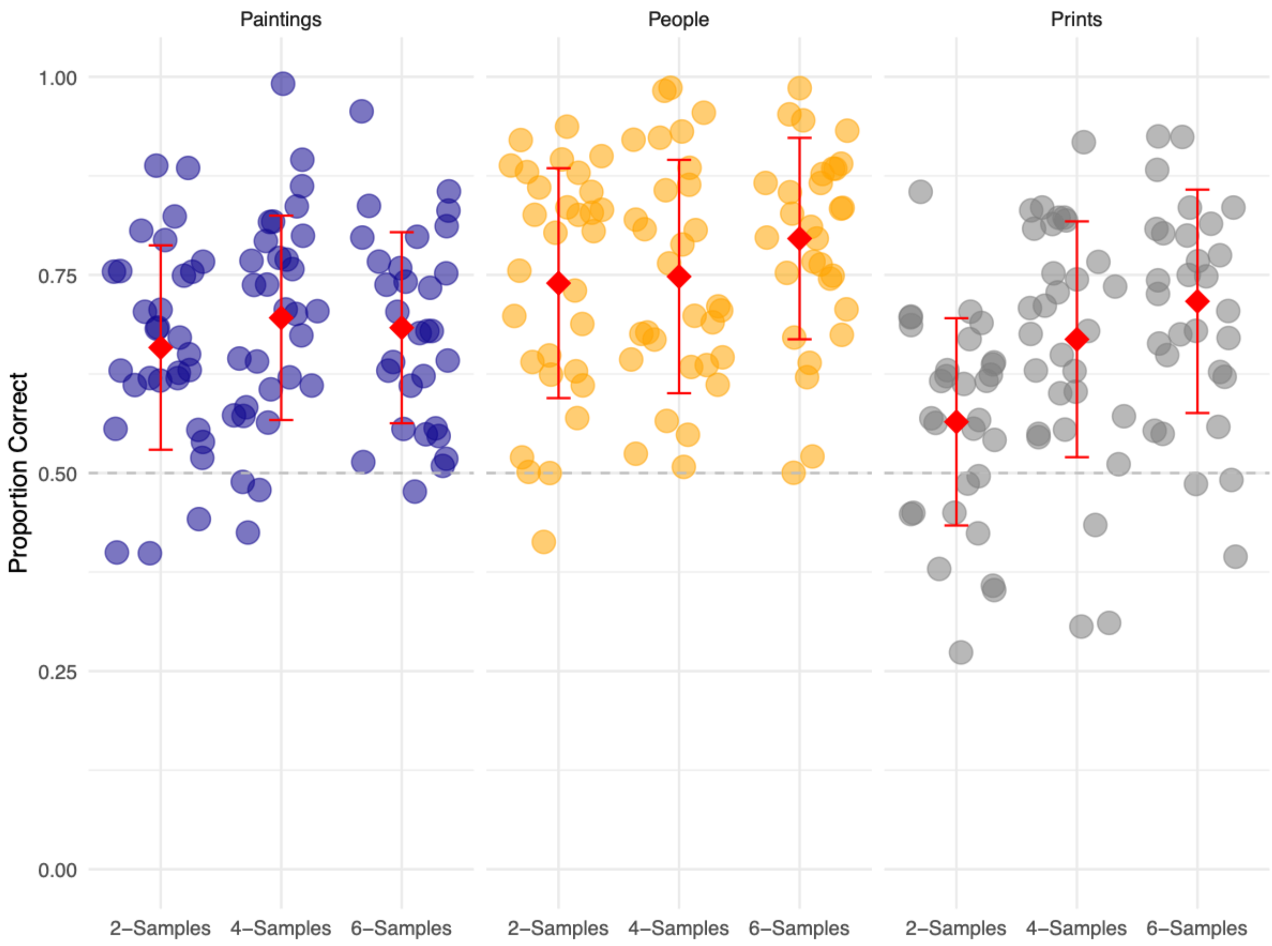
Summary-based encoding models of working memory predict that as informational load increases, participants will rely more on summary statistics to make identification judgements. Therefore, we predicted that participant identification judgements would increase as a function of increasing informational load (increasing summary information) on our identification task.

Participant raw accuracy data is consistent with our prediction. Collapsing across the stimulus sets, proportion correct increased as Information Load increased from two (M = .65, SD = .15), to four (M = .70, SD = .14), to six (M = .73, SD = .14) spotlighted image samples (Figure 2;

for full descriptive statistics on participants' proportion correct scores per Stimulus Type and Information Load conditions, see Appendix B).

Figure 2

Participant Proportion Correct by Information Load and Stimulus Type



Note. Strip plots of participants' proportion correct (y-axis) per Stimulus Type and Informational Load conditions (x-axis). A proportion correct score of 1.00 indicates perfect performance, while score of .50 indicates chance performance. The individual data points reflect the proportion correct scores for individual participants. The different colours indicate Stimulus Type conditions (e.g., purple = paintings; yellow = faces; grey = fingerprints). The red error bars show the mean proportion correct (and standard deviation around the mean) per condition.

Preliminary Analysis - Proportion Correct

The first analysis that was conducted was a preliminary analysis of participants' proportion correct scores using a 3 (Information Load: 2, 4, 6 spotlights) × 3 (Stimulus Type: fingerprints, faces, paintings) repeated measures Analysis of Variance ('ANOVA') to determine if there was a main effect of Information Load on the overall accuracy of participant identification judgements. The results revealed a significant main effect of Information Load (F[2, 58] = 8.54, $p < .001$) and Stimulus Type, $F(2, 58) = 15.97$, $p < .001$ on proportion correct. The interaction between Information Load and Stimulus Type was also significant (F [4,116] = 3.76, $p < .001$). Planned polynomial contrasts further revealed that increased Information Load had a significant positive linear effect on Proportion Correct ($t = 3.61$, $p < .001$), although this effect was less pronounced for paintings (see Figure 2). For this analysis, Mauchly's tests were conducted to check for violations of sphericity (a key assumption of the repeated measures model). The results of these checks showed no evidence of significant deviations; therefore no corrections were made to the reported p values for each effect.

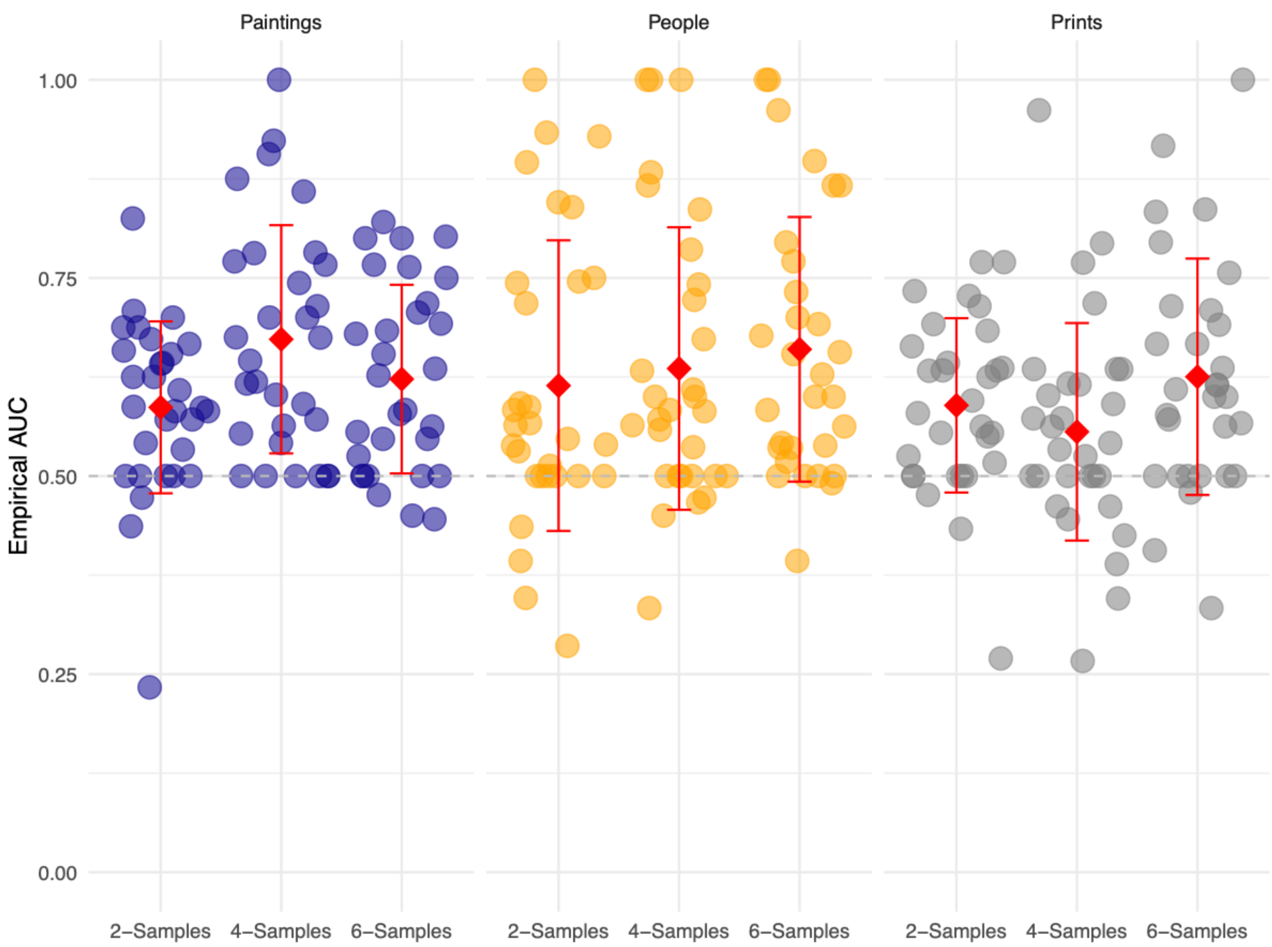
Primary Analysis - Area Under the Curve

While proportion correct informs us of how accurate participants are (i.e., how often they say "Same" and "Different" correctly), it doesn't tell us how sensitive they are to identity information (i.e., how often they say "Same" when the images show the same identity versus how often they say "Same" when the images show different identities). Thus, for our primary analysis, we examined Area Under the Curve ('AUC') as an empirical estimate of each individual participant's sensitivity to identity information. Based on a signal detection framework, AUC is a performance metric that calibrates the trade-off between sensitivity (i.e. the likelihood of hits), and specificity (i.e. the likelihood of correct rejections) to determine how well an individual can distinguish signal (here, visual information that aids correct identification decisions) and noise (visual information that hinders correct identification decisions) from noise in the experiment.

Demonstrating a similar trend to proportion correct, participant raw sensitivity data is consistent with our prediction. Collapsing across stimulus type, proportion correct increased as Information Load increased from two (*M* = .60, *SD* = .14), to four (*M* = .62, *SD* = .16), to six (*M* = .64, *SD* = .15) spotlighted image samples (Figure 3; for full descriptive statistics on participants' AUC scores per Stimulus Type and Information Load conditions, see Appendix C). The fingerprints condition exhibited the most notable change in trend despite these findings (see Figure 3).

Figure 3

Participant AUC scores by Information Load and Stimulus Type



Note. Strip plots of participants' AUC scores (y-axis) per Stimulus Type and Informational Load conditions (x-axis). A score of 1.00 indicates perfect sensitivity to identity, while a score of .50 indicates chance sensitivity to identity. The individual data points reflect the AUC scores for individual participants. The different colours indicate Stimulus Type conditions (e.g., purple = paintings; yellow = faces; grey = fingerprints). The red error bars show the mean proportion correct (and standard deviation around the mean) per condition.

For this primary analysis, the same 3 × 3 repeated measures ANOVA model was used on participant AUC scores to test whether increasing Information Load improved participants' ability to discriminate identities. The results revealed no main effect of Information Load (F[2, 58] = 2.30, p = .11) or Stimulus Type (F[2, 58] = 2.75, p = .072), on participant AUC scores. The interaction between Information Load and Stimulus Type was also not significant, $F(4, 116) = 2.45$, p[GG] = .070. Mauchly's test of sphericity was violated for the Information Load-Stimulus Type interaction (W = .500, p = .023), therefore, the Greenhouse-Geisser correction was reported as the p value of this interaction.

Unplanned Analysis - Correlation

A potential explanation for the disparity in findings between the proportion correct and AUC performance metrics is that AUC accounts for participant confidence ratings, whereas proportion correct does not. Perhaps participant confidence in their decisions is not well calibrated with the accuracy of their decisions, adding noise to the individual AUC scores. We conducted an unplanned exploratory analysis of participants' confidence rating explore this possibility. Firstly, we computed the correction between participants' confidence and their accuracy (proportion correct scores; see Figure 3). Participants' confidence scores were calculated by converting their confidence ratings on the 1-12 scale into a confidence score between 1 and 6 (e.g., ratings of 1 and 12 corresponded with a confidence score of 6/6, and ratings of 6 and 7 corresponded with a confidence score of 1/6). We then conducted a simple correlation analysis to determine if participant confidence was related to their accuracy.

Figure 4

Participant Accuracy-Confidence Correlation

Note. A scatterplot of participants' accuracy (proportion correct; x-axis) relative to their confidence (y-axis). A confidence rating of 6 indicates the participant was "Sure" of their identity decision, while a confidence rating of 1 indicates the participant was "Unsure" of their identity decision. The different colours indicate Stimulus Type conditions (e.g., purple = paintings; yellow = faces; grey = fingerprints). The solid red line of best fit visually indicates the overall trend of the data.

As is demonstrated in Figure 4, the results of this analysis revealed a weak positive correlation between participant confidence and accuracy, $r(267) = .17$, $p = .005$.

Discussion

The purpose of this study was to investigate the extent to which information load affects visual working memory for identity-based information in naturalistic stimuli. Summary-based encoding models of working memory predict that increased information load results in more reliance on summary information in making identification judgements. Thus, we predicted that increasing information load, and thus summary information, in our identity task would improve participant identification judgements.

Preliminary Analysis - Proportion Correct

When we looked at accuracy, we found significant effects of informational load, stimulus type, and of their interaction, on proportion correct. This finding supports summary-based encoding models of working memory (e.g., Ariely, 2001; Parkes et al., 2001) as participants' identification judgements were more accurate as informational load was increased. Thereby suggesting that the increased access to summary statistics diagnostic of identity aided participants in their identification judgements. Thus, the results of this preliminary analysis supported our prediction.

Primary Analysis - Area Under the Curve

When we looked at sensitivity, however, the results revealed no significant effects of informational load, stimulus type, or their interaction, on participant AUC scores. While the results of this primary analysis did not support our prediction, they nevertheless bolstered summary-based encoding models of working memory as sensitivity improved as participants had increased access to summary information.

Performance in the painting condition was consistent across both analyses, and demonstrated a different pattern where participant identification judgements improved from two to four spotlight samples, before declining at six. This finding could potentially be interpreted as supporting discrete resolution models of visual working memory (e.g. Zhang & Luck, 2008), as it appears that identification judgements improved until the capacity limit was reached at four spotlight samples (see Miller (1956); Alvarez & Cavanagh, 2004) where performance declined. On the other hand, this finding could be interpreted as supporting summary-based encoding models, in line with our prediction, in that performance in that particular stimulus condition may have been affected by a greater ratio of noise to signal across informational load conditions compared to fingerprints and faces. That is, participants may have considered that the faces and fingerprints conditions contained information more obviously relevant to their identification decisions compared to paintings where it is less evident which information is helping rather than hindering their decision making. This interpretation was flagged as a possible outcome based on summary-based encoding models of working memory in the introduction.

A compelling explanation as to why these analyses yielded contrary results is the role of participant confidence. While both of the conducted analyses are empirically supported, proportion correct merely informs us how accurate participants are at correctly responding “Same” or “Different” for each trial, whereas AUC delves deeper, analysing the degree to which participants are able to utilise their working memory to cognitively sort “Same” and “Different” identities into their correct categories (see Wixted & Mickens, 2018). AUC further takes into account participant confidence ratings, whereas proportion correct does not. As was revealed in the correlation analysis, participant confidence was only weakly indicative of their accuracy. This suggested that participants rated themselves as not confident in their identification judgements even when accurate, and contrastingly, rated themselves confident when inaccurate, thereby providing an explanation as to why there were no significant findings for the primary analysis in which these confidence ratings were taken into account.

In reflecting on these findings in the context of the experimental design, we considered that perhaps participants found the confidence scale confusing to navigate, or perhaps interpreted it differently than intended. Indeed, examining the collective confidence ratings of the participants revealed extremes on both ends of the confidence rating spectrum. Participants most frequently responded with ratings of 1 and 12 (34.88%), indicating high confidence, and 6 and 7 (23.59%), indicating low confidence (for full breakdown of the frequency analysis of confidence ratings, see Appendix D). This pattern of responding indicates that participants still reported their confidence in binary terms rather than utilising the full breadth of the scale, indicating either full or negligible confidence and largely neglecting middle values. This does not provide a clear representation of their confidence, and this lack of calibration is evidenced in the weak correlation we found between confidence and accuracy. Had participants been less extreme in their confidence ratings, our primary analysis results may have more closely resembled the significant findings of our preliminary analysis.

Participants' tendency to create subcategories within confidence rating scales rather than utilising the full scale is consistent with the previous literature (see e.g., Mickes et al., 2007; Mickes et al., 2011; Tekin & Roedinger, 2017) in which it has been shown that participants have difficulty discriminating between their own high-confidence responses at the highest point of the scale without error feedback (Mickes et al., 2011; see also Tekin & Roedinger, 2017). Mickes et al. (2011) posited that this inability to discriminate between highest-confidence responses may be a result of participants exhibiting "all-or-none recollection" (Yonelinas, 1994), in which stimuli are either entirely recalled or not recalled at all, resulting in binary confidence ratings. This would support discrete resolution models of visual working memory (e.g. Zhang & Luck, 2008). However, the fact that error feedback has been shown to aid participants in scaling their high-confidence responses undermines the strength of this theory (Mickes et al., 2011). Future research may wish to apply signal detection models to further tease out the relationship between accuracy and sensitivity and to explore whether the complexity lies with the role of confidence, or elsewhere (for examples of signal detection theory being applied to forensic contexts see Dunn et al., 2022; Searston et al., 2016).

A second direction for future research could be examining the effect of response bias. As this experiment focused on the role of visual working memory in identification decisions, rather than attempting to correct or train novices out of a particular response bias, any forensic decisions were distanced from their field of origin, and as such, participants were not reminded of the consequences that their decisions would have in a real-world context (e.g., a “Same” decision could condemn an innocent person, and a “Different” decision could let a guilty person walk free). Future research may wish to explore whether such reminders have an effect on response bias.

Despite the discrepancy in the results of the preliminary and primary analyses, our findings nevertheless contribute important information about the role that visual working memory plays in identification decisions, adding to the growing body of literature in this area of research. In particular, there are multiple aspects of the experimental design that promote the generalisability of the findings. The use of naturalistic stimuli in this experiment, rather than simplistic stimuli, as are often utilised in change-detection tasks, enable the findings of this study to be validly considered in the forensic context they are attempting to inform. The use of stimuli conditions covering three different domains (fingerprints, faces, and paintings) further bolster this generalisability, elevating the current research in visual working memory away from basic stimuli and towards a broader range of real-world contexts yet to be explored. Additionally, the choice to utilise non-matching pairings in the fingerprint condition rather than highly similar non-matching pairs, as is customary in fingerprint expertise research, was bolstered by the even spread of data generated across analyses; appearing to have prevented ceiling and floor effects. Finally, the task itself emulates the most crucial aspect of the inspiring forensic context - the accurate matching of fingerprints to their source identity.

In this study, we set out to investigate the effect of informational load on visual working memory in the context of identification tasks utilising complex, naturalistic stimuli. This focus bridges the gap between theoretical models of visual working memory that rely on the use of basic visual stimuli that are not generalisable to real-world contexts, such as fingerprint analysis. Our findings provided support for summary-based encoding models of visual working memory, which suggest that we rely on summary statistics in encoding visual landscapes rather than encoding items completely independently, and that increasing the visual informational load in the process of making identification decisions results in improvements in identification judgements across a broad range of naturalistic stimuli (namely, fingerprints, faces, and paintings). Future research may wish to further investigate these findings by applying signal detection models to explore the complex relationship between confidence and accuracy, or to examine the effects of response bias, especially in a forensic context where identification decisions have significant consequences. Such explorations may bring us closer to understanding how experts are able to achieve such incredible feats utilising their visual working memory.

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Appendix A

Participant Information Sheet

Participant Information Sheet

PROJECT TITLE: The role of visual working memory on identity decisions

HUMAN RESEARCH ETHICS COMMITTEE APPROVAL NUMBER: H-2022-23/64

PRINCIPAL INVESTIGATOR: [redacted]

STUDENT RESEARCHER: [redacted]

STUDENT'S DEGREE: Honours Degree in Psychology

Dear Participant,

You are invited to participate in the research project described below.

What is the project about?

The aim of this project is to better understand the role of visual working memory in decision-making tasks that involve identifying naturalistic stimuli, such as faces, fingerprints, and paintings.

Who is undertaking the project?

This project is being conducted by [redacted]. This research will form the basis for the degree of Honours Degree in Psychology at the University of Adelaide under the supervision of [redacted].

Why am I being invited to participate?

You are being invited as you are a first-year psychology student who meets the following criteria:

- You are at least 18 years of age
- You have the ability to read and understand English
- You have 20/20 or corrected to 20/20 vision
    - You will be required to wear corrective lenses (glasses or contacts) if required to participate in the study
- You have no formal training with fingerprint analysis

What am I being invited to do?

You will be presented with images of faces, fingerprints, and paintings on the screen and will be tested on your memory for these images throughout the experiment.

A responsible University of Adelaide staff member will be available nearby during your session. After you have completed the experiment, the researcher will discuss the study with you and explain the methodology of the experiment, the variables of interest, and will answer any questions you have.

How much time will my involvement in the project take?

Your involvement in this project will take approximately one hour and will take place within the School of Psychology. You will be compensated with course credit.

THE UNIVERSITY of ADELAIDE

Are there any risks associated with participating in this project?

There are no foreseeable risks associated with participating in this project beyond those that you would encounter in everyday life. You will be encouraged to rest your eyes between trials in case of any discomfort experienced from prolonged periods of looking at a computer screen.

What are the potential benefits of the research project?

Participation will help us learn more about the role of visual working memory on identification decisions.

Can I withdraw from the project?

Your participation is completely voluntary. You are free to withdraw from the study at any time and will not be penalised in any way. If, for any reason, you do not want to continue with the experiment, simply let the researcher know. In this event you will still be awarded full credit.

What will happen to my information?

Any information that is obtained from this study and that can be identified with you will remain entirely confidential and will be kept on a password protected computer with multiple redundant backups. The data from this experiment will be identified by a random number upon completion. You will not be identified by this random number, so your performance in this experiment will be recorded, but not associated with you personally. We plan to discuss the results at academic conferences both here and overseas, publish the data in international scientific journals, and store the data in an online open access repository, such as the Open Science Framework, for future meta-analyses and so that other researchers can easily reproduce our work. In any publication, presentation or online record, you cannot be identified.

Your information will only be used as described in this participant information sheet and it will only be disclosed according to the consent provided, except as required by law.

Who do I contact if I have questions about the project?

Any questions about the project can be forwarded to [redacted] (Primary Supervisor) at [redacted] or [redacted] at [redacted] (Student Researcher).

For any questions about the ethical conduct of research, please contact Dr Paul Delfabbro, Chair of the Low Human Research Ethics Subcommittee in the School of Psychology (paul.delfabbro@adelaide.edu.au).

If I want to participate, what do I do?

If you would like to participate, please provide your student ID number and email address on the consent form to be provided with course credit as compensation for your time.

Yours sincerely,

[redacted] (Student Researcher) and [redacted] (Primary Supervisor)

Appendix B

Table B1

Means and Standard Deviations for Proportion Correct (Informational Load by Stimulus Type)

Informational Load	Paintings		People		Prints	
	M	*SD*	*M*	*SD*	*M*	*SD*
2	.66	.13	.74	.15	.56	.13
4	.70	.13	.75	.15	.67	.15
6	.68	.12	.80	.13	.72	.14

Note. Table depicting descriptive statistics of participants' proportion correct per Informational Load (horizontal rows as indicated by the leftmost column), and Stimulus Type (vertical columns as indicated) conditions.

Appendix C

Table C1

Means and Standard Deviations for AUC Scores (Informational Load by Stimulus Type)

Informational Load	Paintings		People		Prints	
	M	*SD*	*M*	*SD*	*M*	*SD*
2	.59	.11	.61	.18	.59	.11
4	.67	.14	.64	.18	.56	.14
6	.62	.12	.66	.17	.63	.15

Note. Table depicting descriptive statistics of participant AUC scores per Informational Load (horizontal rows as indicated by the leftmost column), and Stimulus Type (vertical columns as indicated) conditions.

Appendix D

Table D1

Frequency Analysis of Participant Confidence Ratings

Confidence Rating	Frequency of Response	Percentage of Response
1	812	.19
2	146	.03
3	222	.05
4	240	.06
5	261	.06
6	549	.13
7	470	.11
8	248	.06
9	272	.06
10	268	.06
11	129	.03
12	695	.16

Note. Table depicting the results of a frequency analysis conducted on participant confidence ratings. The frequency and percentage of total responses corresponds with the numerical confidence rating in the leftmost column. Frequency of response, as depicted in the middle column, indicates the number of times that participants responded with each confidence rating. The total number of confidence ratings was 4,320. Percentage of response, as depicted in the rightmost column, indicates the relative percentage of frequency that each confidence rating was selected.

Appendix E

Research Plan

Psychology Honours Project 2023 – Research Plan
Student Name: [redacted]
Student ID: a1726701

Study Information

1. Title: The nature of visual working memory for identity decisions

2. Target Journal: Cognitive Research: Principles and Implications

3. Research Aim/s:

The aim of this project is to better understand the nature of visual working memory in tasks that involve identifying individuals from naturalistic stimuli, such as fingerprints. Specifically, we will investigate how varying the level of informational load on the encoding of naturalistic images impacts identity judgements.

4. Research Question/s:

To what extent does information load affect visual working memory for identity-based information in naturalistic stimuli?

5. Use of Theory:

While there are theoretical models of visual working memory that have been thoroughly tested with basic visual displays (e.g., colour, line orientation, objects) in a change detection paradigm (e.g. Miller, 1956, Ma et al., 2014, Brady & Tennenbaum, 2013), the nature of visual working memory in real-world contexts that call for identification judgements based on naturalistic stimuli (e.g. fingerprints), is still largely unexplored. This gap is significant as visual working memory has been shown to be a hallmark feature of expert judgments in domains like fingerprint analysis where examiners are tasked with deciding if two different fingerprints were left by the same finger (Thompson & Tangen, 2014).

This project seeks to fill this knowledge gap by investigating how one aspect of visual working memory — informational load at the encoding stage — affects identity judgments in an identity detection paradigm with three kinds of naturalistic stimuli: fingerprints, faces, and paintings.

In a typical change detection task of the sort commonly used in visual working memory research, observers are presented with a visual display of discrete objects, followed by a mask and then a second presentation of the same visual display. The critical manipulation is a single change to one of the discrete objects in the secondary display. Observers' sensitivity to these small changes under various conditions is used to understand their mental representations of the initial display.

This template is modified from Haven, Tamarinde L. & Van Grootel, Leonie. (2019). Preregistering qualitative research. 10.1080/08989621.2019.1580147.

In our identity detection paradigm, the task is fundamentally the same, except instead of making a single change to a discrete object in the visual display at hand, the identity of the individual depicted in the image changes. In the case of fingerprints, observers see an image of a fingerprint, followed by a mask, then a second image of a fingerprint. The second fingerprint is always a different image, and the task is to decide if it was left by the same individual as the first fingerprint or not. There is evidence that novices and experts are able to perform this task successfully well above chance (Thompson & Tangen, 2014). The question we address in this project is, to what extent is working memory for such identity-based information affected by the information load in the first display?

Below is a brief description of a few different models of visual working memory from the psychology literature as to how they differ in terms of predicting performance in an identity memory task:

- Flexible resource models (e.g. Alvarez & Cavanagh, 2004; Bays & Husain, 2008)
    - As informational load increases, performance decreases.
    - Information thought to be of higher relevance will be recalled with more precision, at the cost of information deemed less relevant.
    - Experts are more efficient with memory recognition tasks due to their superior deployment of attention, and more proficient cognitive sorting of relevant and irrelevant information.
- Discrete resolution models (e.g. Zhang & Luck, 2008)
    - As informational load increases, performance increases. Once the capacity limit of information slots has been reached, performance declines.
    - Visual working memory has a fixed number of slots of information, thought to be 4 or 5, that can each hold only a single item, with a fixed level of detail.
    - Items are either encoded, and thus remembered, or not encoded, and forgotten entirely.
- Chunking models (e.g., Chase & Simon, 1973)
    - As informational load increases, if an individual has domain-specific expertise, their performance increases compared to individuals without relevant expertise.
    - Performance is dependent on expertise and how well individuals can chunk the informational load.
    - If participants have expertise in a domain (fingerprints, faces, paintings), they exhibit more efficient encoding and retrieval of domain-relevant information, resulting in better performance.
- Summary-based encoding models (e.g., Ariely, 2001; Parkes et al, 2001)
    - As informational load increases, performance increases.
    - Participants rely on summary information to inform which details to encode.
    - Performance will either improve as informational load increases by virtue of greater access to summary information diagnostic of identity or will depend on how relevant the summary information is towards identification decisions. This may differ across the different stimuli (fingerprints, faces, paintings).

In accordance with summary-based encoding models, we predict that identification judgements will improve as informational load is increased because of the abundance of summary information relevant to determinations of identity.

Design Plan

6. Tradition (optional): N/A

7. Study Design:

The study design is a 3 (informational load: 2, 4, or 6 visual chunks) x 3 (stimulus type: fingerprints, faces, paintings) fully within-subjects experimental design.

In each experimental block, participants will complete 48 trials, with a random half of those trials (24) featuring a different target image of the same identity (finger, individual, or artist) to that of the display of visual chunks. The other half of trials will feature a target image of an entirely different identity to the display of visual chunks. The trial order within each block will be randomized for each participant.

8. Study Measures (optional):

Participants will respond on a 12-point forced-choice confidence rating scale ranging from 1 (Sure Different) to 12 (Sure Same). The mid points of the scale indicate 6 (Unsure Different) and 7 (Unsure Same). These confidence ratings will be used to compute the empirical Area Under the Curve (AUC), which constitutes the primary measure of participant sensitivity to changes in identity across trials.

9. Study Materials (optional):

The images used in the fingerprint block will be randomly sampled from a large set of fully rolled prints. The images from the faces and paintings blocks will also be sampled in this manner. As the trials progress, the visible display of chunks will be increased from 2, to 4, to 6 chunks. These chunks will be sampled from a 2x6 grid using a 150x150 circular mask in Adobe Photoshop.

10. Study Procedure:

Participants will complete a series of trials of a recognition memory task that involves observing a display of 2, 4, or 6 visual chunks of a fingerprint for 5 seconds, followed by a scrambled mask, fixation point, and finally a target image of a full fingerprint. Participants will then be prompted to indicate whether they believe that the target fingerprint image was left by the same finger or a different finger to the initial display of visual chunks.

Participants will repeat this task over three blocks of trials with three different types of visual stimuli: fingerprints, faces, and paintings. In the face block, participants will be asked to indicate whether they believe that the target image of the full face represents the same or a different person as the initial display of visual chunks. Finally, in the painting block, participants will be asked to indicate if the target painting image depicts a work by the same or different artist to the initial display of visual chunks. The order of these three blocks will be randomized and counterbalanced across participants.

This template is modified from Haven, Tamarinde L. & Van Grootel, Leonie. (2019). Preregistering qualitative research. 10.1080/08989621.2019.1580147.

Sampling Plan

11. Existing Data/Partial Existing Data/Original Data

Original data will be collected for this project.

12. Data Collection Procedures:

Participants will be First-Year Psychology students recruited through the Research Participation System, who will participate in the project in return for course credit.

13. Type of Data Collected:

Behavioural responses

14. Sample Size:

A power analysis was conducted to estimate the sample size required for a repeated measures ANOVA. The analysis indicated that for a moderate to large effect size (typical of fingerprint and visual working memory experiments) 12 – 28 participants will be required.

15. Stopping Rule:

Data collection will be stopped once 28 participants has been reached, or by the end of the second week of semester 2 (Friday 4 August).

Analysis Plan

16. Data Analyses:

<u>Data Analysis Method</u>

A 3 (informational load: 2, 4, or 6 visual chunks) x 3 (stimulus type: fingerprints, faces, paintings) repeated measures ANOVA will be conducted on participant AUC scores in R, with planned contrasts to test the above hypotheses.

Either treatment or sum-to-zero contrasts will be used to test for differences in sensitivity between stimulus type conditions, contrasting fingerprints/faces, and fingerprints/paintings. This type of contrast will use fingerprints as a pseudo control condition, given that it is the motivating context of the project.

Polynomial contrasts will be used to describe the overall trend for the informational load factor levels, comparing the 2, 4, and 6 visual chunks blocks to observe how sensitivity to identity changes with increasing informational load.

This template is modified from Haven, Tamarinde L. & Van Grootel, Leonie. (2019). Preregistering qualitative research. 10.1080/08989621.2019.1580147.

Data Exclusion Criteria

As an attention check, the data from any participants who provide the same score on 90% or more answers of the forced-choice survey will be excluded.

Other

17. Other (Optional):

References

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Research Plan Checklist

Students: This checklist must be completed and signed by your primary supervisor as a requirement of the research plan component of the thesis. Please append a signed copy of the completed checklist to your research plan document and submit them together (as a single PDF document) via the MyUni assignments tab no later than **9am 15th of May**. To ensure your supervisor has sufficient time to review your research plan and complete the checklist, we encourage you to provide them with a copy of the checklist and a draft of your research plan as early as possible — at least one week before the due date. We also encourage you to work with supervisors to develop your research plans from early on in the semester.

Supervisors: Research plans for honours projects should be well reasoned and well thought-out (sound), and also manageable within the scope of the timeline, available resources and the student's capabilities (feasibility). Please review the student's research plan (template provided on MyUni) and indicate if each step of their plan is sound and feasible by ticking the appropriate box. If the component is not applicable given the nature of the project please tick "Not Applicable". If any step of the plan is not yet sound or feasible please leave the box/s unticked.

Study Information	Not Applicable	Feasible	Sound
Title	☐	☐	☑
Target Audience	☐	☐	☑
Research Aim/s	☐	☐	☑
Research Question/s	☐	☐	☑
Use of Theory	☐	☐	☑

Design Plan	Not Applicable	Feasible	Sound
Tradition	☑	☐	☐
Study Design	☐	☑	☑
Study Measures	☐	☑	☑
Study Materials	☐	☑	☑
Study Procedure	☐	☑	☑

Sampling Plan	Not Applicable	Feasible	Sound
Data Collection Procedures	☐	☑	☑
Type of Data Collected	☐	☑	☑
Sample Size	☐	☑	☑
Stopping Rule	☐	☑	☑

Analysis Plan	Not Applicable	Feasible	Sound
Data Analyses	☐	☑	☑

Other	Not Applicable	Feasible	Sound
	☑	☐	☐

Student Name	Signature	Date
[redacted]	[redacted]	12/5/2023

Primary Supervisor Name	Signature	Date
[redacted]	[redacted]	12/5/2023